JOINT TRANSCEIVER OPTIMIZATION IN WIRELESS MULTIUSER MIMO-OFDM CHANNELS BASED ON SIMULATED ANNEALING

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ABSTRACT

In this paper we address the problem of joint transmitter and receiver optimization in a wireless multiuser MIMO-OFDM environment. We consider a centralized design strategy assuming that Channel State Information (CSI) is available. The optimization goal is the minimization of the total transmitted power subject to different constraints, such as the Quality of Service (QoS) for each user in terms of the mean Bit Error Rate (BER) or the maximum power for each transmitter. In this design, the physical resources are used in an optimum way and the Multiple Access Interference (MAI) is minimized. The proposed technique is a variant of the Simulated Annealing (SA) algorithm, which is able to find the global optimum. Besides, it can handle all kind of constraints by generalizing the definition of the cost function. Finally, we present simulation results and compare this technique with a Lagrange-gradient based solution.

1 INTRODUCTION

In last years, special attention has been given to the joint use of smart antennas at both the transmitter and receiver, configuring a Multi-Input-Multi-Output (MIMO) channel. The new standards such as [1], tend to specify very high frequencies for the front-end and Radio-Frequency (RF) chains, permitting the use of multiple antennas at both the Access Points or Base Stations (BSs), and the Portable or Mobile Terminals (MTs). Additionally, the Orthogonal Frequency Division Multiplexing (OFDM) modulation has been proposed for several broadcasting and communications systems such as the European WLAN Hiperlan/2 [1].

There is also an increasing demand for higher capacity or number of users, and Quality of Service (QoS) in terms of bit-rate and Bit Error Rate (BER). Recently, several approaches have been proposed to exploit the MIMO-OFDM configuration from a single-user point of view [2] [3]. However, one of the main capacities of this structure is that it is possible to implement the Space Division Multiple Access (SDMA), which means that several users can access the radio channel at the same time and at the same frequency. In this paper we analyze the design problem corresponding to the joint optimization of the receivers and transmitters in a scenario with several parallel communications, assuming that Channel State Information (CSI) is available at all the terminals. Under this consideration, it is proposed a simplified single-user detector for the receivers in Section 2, and a joint design for the transmit beamvectors in Section 3. The goal is the minimization of the total required transmit power subject to different constraints, such as the maximum BER for each user or communication, and/or the maximum power for each transmitter. This optimization problem is difficult to solve and there are no closed expressions for it. Here we propose a heuristic search of the optimal design based on a variant of the Simulated Annealing (SA) algorithm and compare its behavior with a Lagrange-gradient based technique by means of simulation results in Section 4.

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2 SYSTEM AND SIGNAL MODELS

2.1 System and Signal Models

We consider the general case in which K users or communications are coexisting in the same area, and working in the same time-slot and frequency band. The modulation format is assumed to be a N-carrier OFDM. In the scenario there are several terminals, and each of them is able to transmit and/or receive, and have more than one antenna. In this paper we address the case corresponding to single-hop point-to-point links, in which each communication is assigned to a single transmitter and a single receiver, however the extension to the case of point-to-multipoint or multipoint-to-point (the same communication is carried out by several receivers and/or transmitters) links and multi-hop networks is direct. In the case we analyze, one terminal can be engaged to more than one communication. In the following, the words "link", "communication" and "user" are used as synonyms.

The snapshot vector signal model for the kth user at the nth carrier is [2]:

$$\mathbf{y}_n^{(r(k))}(t) = \sum_{l=1}^{K} \mathbf{H}_n^{(t(l),r(k))} \mathbf{b}_n^{(l)} s_n^{(l)}(t) + \mathbf{n}_n^{(r(k))}(t) \quad (1)$$

where $r(k)$ represents the terminal detecting the symbols from the kth communication, and $t(l)$ is the element transmitting the signal corresponding to the lth link. The number of components of $\mathbf{y}_n^{(r(k))}(t)$ and $\mathbf{b}_n^{(l)}$ is the number of antennas of the $r(k)$th and $t(l)$th terminals, respectively. $\mathbf{b}_n^{(l)}$ represents the beamvector applied to $s_n^{(l)}(t)$, which is the transmitted data in the nth carrier in the tth OFDM symbol for the lth communication, where it is considered

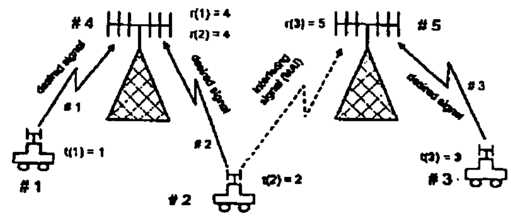

Figure 1: Typical configuration in a multiuser MIMO-OFDM scenario with 3 users or communications.

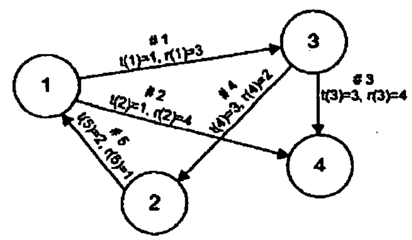

Figure 2: General configuration with several terminals and p-to-p links.

that it is normalized: $E\{|s_n^{(l)}(t)|^2\} = 1$. $E\{\cdot\}$ stands for the mathematical expectation operator. The matrix $\mathbf{H}_n^{(t(l),r(k))}$ represents the MIMO channel for the nth carrier between the $t(l)$th and the $r(k)$th terminals. Finally, the vector $\mathbf{n}_n^{(r(k))}(t)$ models the contribution of noise plus interferences from outside the system at the $r(k)$th receiver at the nth frequency, where its associated covariance matrix is $\phi_n^{(r(k))} = E\left\{\mathbf{n}_n^{(r(k))}(t)\mathbf{n}_n^{(r(k))^H}(t)\right\}$. $(\cdot)^H$ stands for complex conjugate transpose.

This signal model can be easily adapted to well-known systems such as cellular communications (both the uplink and downlink channels, see Fig. 1), and also to the emerging reconfigurable adhoc networks. Fig. 2 shows a general configuration with 4 terminals and 5 communications.

2.2 Single-User Receiver Optimization

As far as the receiver is concerned, the optimum design should be based on a multiuser detector; however, in most practical cases this is unaffordable since the associated computational load is too high; therefore in this work we propose single-user receivers. The optimum receive beamvector $\mathbf{a}_n^{(k)}$ for the kth user at the nth carrier is the one that maximizes the Signal-to-Noise and Interference Ratio (SNIR) [2]:

$$\mathbf{a}_n^{(k)} = \alpha_n^{(k)} \mathbf{R}_n^{(k)^{-1}} \mathbf{H}_n^{(t(k),r(k))} \mathbf{b}_n^{(k)} \quad (2)$$

$$\mathbf{R}_n^{(k)} = \phi_n^{(r(k))} + \sum_{\substack{l=1 \\ l\neq k}}^{K} \mathbf{H}_n^{(t(l),r(k))} \mathbf{b}_n^{(l)} \mathbf{b}_n^{(l)^H} \mathbf{H}_n^{(t(l),r(k))^H} \quad (3)$$

The estimates of the transmitted symbols are calculated as follows: $\hat{s}_n^{(k)}(t) = \mathrm{dec}\left\{\mathbf{a}_n^{(k)^H} \mathbf{y}_n^{(r(k))}(t)\right\}$, where $\mathrm{dec}\{\cdot\}$ stands for decision. The SNIR at the detection stage for the kth user at the nth carrier is [2]:

$$\mathrm{SNIR}_n^{(k)} = \mathbf{b}_n^{(k)^H} \mathbf{H}_n^{(t(k),r(k))^H} \mathbf{R}_n^{(k)^{-1}} \mathbf{H}_n^{(t(k),r(k))} \mathbf{b}_n^{(k)} \quad (4)$$

Taking into account this result, in OFDM it is defined the effective BER as the BER averaged over all the subcarriers: $\mathrm{BER}^{(k)} = \frac{1}{N}\sum_{n=0}^{N-1} Q\left(\sqrt{k_m \mathrm{SNIR}_n^{(k)}}\right)$, where we have assumed that the interferences are approximately Gaussian distributed, and k_m depends on the modulation applied to each subcarrier (for BPSK, $k_m = 2$).

3 SIMULATED ANNEALING BASED TRANSMITTER OPTIMIZATION

In last section we have derived low computational cost single-user receivers, and now we provide techniques for the design of the transmit beamvectors $\mathbf{b}_n^{(k)}$ subject to QoS constraints. Obviously, a very important parameter is the required power. In case of using several transmit antennas, the power used for transmitting the information symbol corresponding to the nth carrier of the kth user is proportional to $\|\mathbf{b}_n^{(k)}\|^2$. As far as the QoS requirements is concerned, here we apply constraints directly in terms of the effective BER for each user, and so we have K constraints. For the kth user we specify which is the maximum effective BER $\gamma^{(k)}$ as follows:

$$\mathrm{BER}^{(k)} \leq \gamma^{(k)} \quad k = 1,\ldots,K \quad (5)$$

Under these constraints, our goal is the minimization of the total transmitted power P_T: $P_T\left(\{\mathbf{b}_n^{(k)}\}_{n=0,\ldots,N-1}^{k=1,\ldots,K}\right) = \sum_{k=1}^{K}\sum_{n=0}^{N-1}\|\mathbf{b}_n^{(k)}\|^2$. This formulation generalizes the results presented in [4], where the design was based on a multiuser uplink MC-CDMA scenario with one antenna at the transmitter and receiver. The QoS constraints were formulated in terms of the SNIR instead of the BER. In [5] the transmit power was stated to be a prefixed value, and the goal was the optimization of the mean quality for all the users, so no QoS could be guaranteed for each communication, and the physical resources were not used in an optimum way as no power allocation was carried out. In [6] these results were extended to the most general case and an iterative algorithm was proposed, although it was shown that the deduced technique might converge to a suboptimal solution.

Besides the previous stated QoS constraints, it could be convenient in some scenarios, to add constraints corresponding to the maximum transmit power in some equipments, such as the battery-limited MTs in an uplink transmission in a cellular system. In this case we generalize this consideration and define the transmitted power for the ith equipment as: $P_T^{(i)} = \sum_{\substack{k=1 \\ t(k)=i}}^{K}\sum_{n=0}^{N-1}\|\mathbf{b}_n^{(k)}\|^2$. In our problem we add this kind of constraints (not considered in [4], [5] and [6]) to some of the transmitter equipments. Let us define T as the set of transmitter elements to which it is applied the maximum transmit power constraint. Hence, these are formulated as $P_T^{(i)} \leq P_{\max}^{(i)} \quad i \in \mathrm{T}$.

There are no closed expressions for the stated constrained optimization problem. Some previous works propose gradient search algorithms to find a solution [4] or other kind of iterative methods [5] [6], but in general, this kind of strategies may find a local suboptimum minimum due to the non-convexity behavior of the optimization problem, as it was

shown in [6]. Besides, the gradient techniques may have some convergence problems related with the speed and the convergence itself [4] [7], and require that the constraints are differentiable, limiting their application. In this paper we propose the use of the heuristic search algorithm Simulated Annealing (SA) to find the global optimum point taking into account all the constraints previously specified. We suppose that a feasible solution exists, that is, a collection of transmit beamvectors that satisfies all the constraints simultaneously. In case this is not possible, the algorithm will not converge to any acceptable design.

SA is an iterative process able to find the optimum solution, even when the problem is non-convex. This algorithm has analogies with the annealing of solids in physics as it is explained in [8]. In our problem, in each step there is a collection of beamvectors $\{\mathbf{b}_n^{(k)}\}_{n=0,\ldots,N-1}^{k=1,\ldots,K}$ which is called the current solution. Given the current solution (which is equivalent to a concrete particles arrangement or state in physics) a new solution or collection of beamvectors is proposed. If it is "better" than the original one, then it is retained as the current one. On the contrary, if it is "worse", then the proposed solution is accepted with a certain probability. This means that "worse" solutions may be accepted. This mechanism, called "hill-climbing", is important so as to avoid finding a suboptimal solution or local minimum. The parameter that controls this acceptance probability is the temperature T, as in the case of annealing in physics. The higher the temperature, the higher the acceptance probability. The temperature is lowered step by step, so that asymptotically only "better" solutions are accepted and a minimum is approached. The meaning of "better" and "worse" is related with the definition of a cost function $f(\cdot)$ that depends on the transmit beamvectors, and which corresponds to the energy of a state in the annealing in physics.

Here we summarize the basic ideas of the SA algorithm that we propose to solve the stated optimization problem. In this case, we apply the algorithm to a continuous solution space. Besides, the cost function $f(\cdot)$ depends on the temperature T (6):

- *Cost function definition:*

$$f\left(\{\mathbf{b}_n^{(k)}\}\right) = P_T + \frac{\alpha}{T}\sum_{k=1}^{K}\left(\log\frac{\mathrm{BER}^{(k)}}{\gamma^{(k)}}\right)^{+2} + \frac{\alpha}{T}\sum_{i\in T}\left(\log\frac{P_T^{(i)}}{P_{\max}^{(i)}}\right)^{+2} \qquad (6)$$

where $(x)^+ = x$ if $x \geq 0$ and 0 if $x < 0$.

- *Proposed solution generation:*

$$\begin{aligned}\widehat{\mathbf{b}}_n^{(k)} &= \mathbf{b}_n^{(k)} + \mathbf{w}_n^{(k)}, \quad n = 0,\ldots,N-1, k = 1,\ldots,K \\ \mathbf{w}_n^{(k)} &\sim \mathrm{Gauss}(0, \sigma_b^2\mathbf{I}) \end{aligned} \qquad (7)$$

- *Probability of acceptance of the proposed solution:*

$$\mathrm{Prob} = \exp\left\{-\frac{1}{T}\left(f\left(\{\widehat{\mathbf{b}}_n^{(k)}\}\right) - f\left(\{\mathbf{b}_n^{(k)}\}\right)\right)^+\right\} \quad (8)$$

- *System cooling:* The temperature is lowered with an exponential profile:

$$T \leftarrow \beta T \quad \beta \cong 0.99 \qquad (9)$$

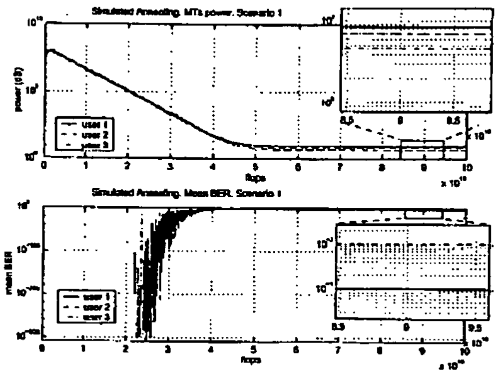

Figure 3: Performance of the Simulated Annealing in scenario 1.

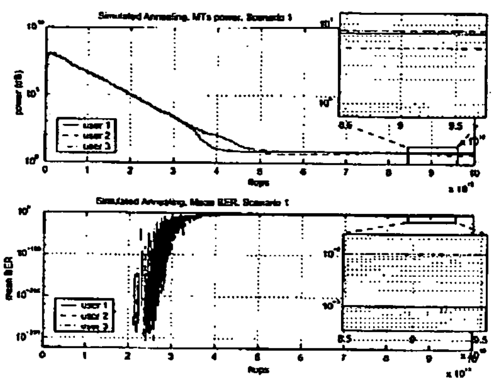

Figure 4: Performance of the Simulated Annealing in scenario 1. Power constraint in MT 1.

Initially the temperature T must be high enough so that most of the proposed solutions are accepted. In this paper we run 100 iterations per each value of T. The cost function is equal to the total transmit power plus a quadratic penalty term that takes into account if the BERs are greater than the required ones, and if the individual transmit powers are greater than those specified. As T is lowered, the penalty term is increased, and so, we asymptotically avoid solutions that do not fulfill the constraints. We make relative comparisons of the BER and transmit powers with the required values by means of the $\log(\cdot)$ function, as experimentally we have observed that it behaves better than absolute comparisons; however, other kinds of penalty functions could have been used. The proposed solutions are generated by applying independent complex circularly symmetric Gaussian noise to the components of the beamvectors. The acceptance ratio is monitorized per each value of T. In case it is lower than 0.1 for 5 times, then the variance of the Gaussian noise is lowered

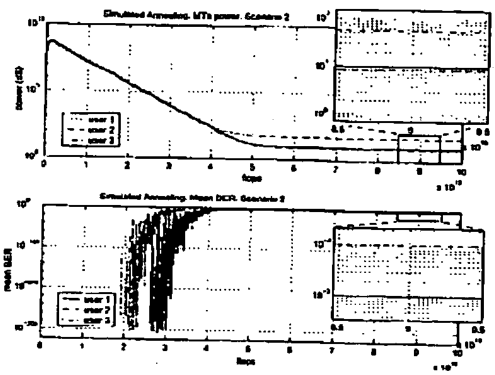

Figure 5: Performance of the Simulated Annealing in scenario 2.

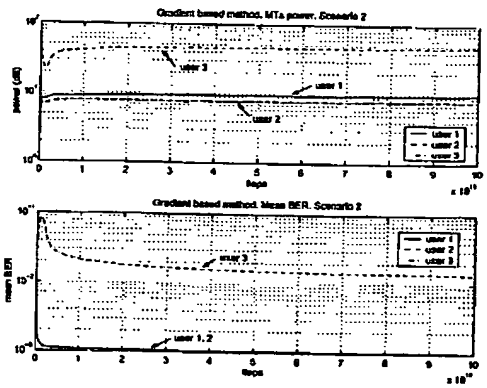

Figure 6: Performance of the gradient based algorithm in scenario 2.

by means of an exponential rule ($\sigma_\delta^2 \leftarrow 0.95\sigma_\delta^2$). This helps the algorithm to find with more precision the minimum as the temperature is lowered, and so, it increases significantly the convergence rate of the technique.

In the next section we make comparisons between the proposed SA technique and a gradient solution based on the Lagrange multiplier method and the quadratic penalty function [4] [7]. In this gradient solution, we only take into account the QoS constraints. Under this assumption, it can be shown that the minimum transmit power can be achieved when the constraints are fulfilled with equality. The technique is based on the definition of the Lagrangian expression $L = P_T + \lambda \sum_{k=1}^{K} \left(\log \frac{\mathrm{BER}^{(k)}}{\gamma^{(k)}}\right)^2$ and the results deduced in [4]. One important problem of this gradient technique is that a step-size parameter μ must be adjusted, and that, as it will be shown in the next section, the speed of convergence of this technique decreases importantly as the design approaches the constraints. Besides, a suboptimal minimum may be achieved instead of the global optimum design.

4 SIMULATION RESULTS AND CONCLUSIONS

In this section we simulate an uplink channel with 3 MTs and 1 BS. The OFDM modulation consists of 16 carriers and both the MTs and BSs have 5 antennas. The QoS constraints in terms of the mean BER are 10^{-3}, 10^{-3} and 10^{-2} and $\alpha = 100$. In the first scenario, we assume that the path-loss is very similar for all the users. In Fig. 3 we show the power for the 3 users and the BER, concluding that the algorithm is able to find a design fulfilling the constraints when no power constraints are applied. The power corresponding to the first user is 8.45 W, and the total power is 20.1 W. If we apply a power constraint to the first user equal to 8 W, then the results are those shown in Fig. 4. We conclude that in this case the algorithm allocates 7.6 W to the first user, whereas the others increase their corresponding consumption. In this case the global transmit power has increased up to 20.8 W.

In Fig. 5 and 6 we show the results for an scenario in which the third user has a path loss with respect to the first two users equal to 12 dB. Fig 5 corresponds to the application of SA, whereas Fig. 6 corresponds to the gradient-based algorithm with a μ parameter equal to 0.001. We conclude that with the same computational load, the SA can fulfill the constraints, whereas the gradient based technique decreases importantly the speed of convergence as the solution is nearer from them.

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